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Rebound effects in UK road freight transport

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ABSTRACT

This paper analyses aggregate time-series data to estimate the direct rebound effect in UK road freight over the period 1970–2014. We investigate 25 different model specifications, conduct a comprehensive set of diagnostic tests to evaluate the robustness of these specifications and estimate the rebound effect using three different elasticities. Using the mean of the statistically significant estimates from these specifications, we estimate a direct rebound effect of 61% - which is larger than previous estimates in the literature and almost twice as large as the consensus estimate of direct rebound effects in road passenger transport. Using the mean of the estimates from our most robust models, we estimate a slightly lower direct rebound effect of 49%. Our estimates are fairly consistent between different model specifications and different metrics, although individual estimates range from 21% to 137%. We also find that an increasing proportion of UK road freight is being undertaken by foreign registered vehicles, and that increases in the vehicle weight limits have encouraged more freight activity. We highlight the significant limitations imposed by the use of aggregate time series data and recommend that further studies in this area employ data from vehicle use surveys.

1. Introduction

In 2015, freight transport accounted for 6% of global energy consumption and one third of transport energy consumption (IEA, 2016). Although road transport by heavy goods vehicle (HGV) accounted for only around one quarter of global freight activity (in tonne kilometres), it was responsible for nearly three quarters of energy use for freight transport and around one quarter of energy use for road transport. Energy use for freight transport is growing faster than for passenger transport and the scope for substituting towards low carbon fuels is limited. But despite this, freight transport tends to be neglected by both researchers and policymakers.

Historically, freight activity has grown in line with economic activity, along with the associated energy consumption. However, in the past three decades there has been some decoupling of freight activity from GDP in OECD countries, partly a result of economic restructuring and the outsourcing of manufacturing to emerging economies (McKinnon, 2007; Tapio, 2005). While increased consumption of material goods tends to increase freight activity, the relationship between the two is mediated by a range of factors, several of which have undergone major changes in recent years. These include, for example, shifts towards lighter commodities, wider sourcing of products, the growth of just-in-time distribution, increases in packaging volume and greater concentration of manufacturing and stockholding (Lehtonen, 2008). In turn, energy consumption for road freight has been affected by additional changes in logistics, driving patterns, road congestion, the amount of empty running and the average size, fuel efficiency and load factor of HGVs (Sorrell et al., 2009, 2012).

With fuel costs accounting for up to one third of operating costs (Freight Transport Association, 2017), freight operators have a strong economic incentive to minimise fuel consumption. But while more fuel-efficient vehicles (i.e. less fuel use per vehicle

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kilometre) can contribute towards this end, operational factors such as the average size of vehicles (maximum loaded weight) and the average load factor of those vehicles (ratio of average to maximum loaded weight) tend to be more important (Sorrell et al., 2009, 2012). In the case of UK road freight, average fuel use per tonne kilometre has fallen over the last 30 years while fuel use per vehicle kilometre has remained relatively static (Sorrell et al., 2012). With the exception of changes in road fuel duty, public policy measures to reduce carbon emissions from transport have had little influence on these trends.

Improvements in the fuel efficiency of road freight should reduce the cost of road freight, which may in turn encourage increased demand for road freight (more tonne kilometres) - thereby offsetting some of the potential energy and carbon savings. This is termed the ‘direct rebound effect’. Analogous effects occur in road passenger transport and have been extensively studied over the last 20 years. For example, a meta-analysis of the results from 76 studies of car transport found a mean long-run direct rebound effect of 32% - implying that one third of the potential energy savings from more fuel-efficient cars had been offset by increased driving (Dimitropoulos et al., 2016). But to date, only a handful of studies have investigated whether comparable rebound effects occur within the road freight sector.

This paper therefore seeks to contribute to the limited literature in this area by estimating the direct rebound effect for UK road freight over the period 1970–2014. The following section provides further background on this topic and summarises the empirical estimates that have been made to date. Section 3 describes our methodology, including the specification of the econometric models and the robustness tests used to select between them. Section 4 summarises our data sources and discusses the trends in the relevant variables. Section 5 presents our results, including the estimated rebound effects. The paper concludes by highlighting the limitations of our approach and the priorities for future research.

2. Background

Rebound effects in road transport are commonly investigated through econometric analyses of aggregate data on fuel use and travel patterns. This approach allows the rebound effect to be estimated from one or more elasticities, derived from the estimated parameters of the regression equation. The most obvious measure is the elasticity of demand for the relevant energy service (S) with respect to some measure of energy efficiency (ε): $\eta_\varepsilon(S)$. The elasticity of the demand for energy (E) with respect to energy efficiency ($\eta_\varepsilon(E)$) is then given by (Sorrell and Dimitropoulos, 2007):

$$\eta_\varepsilon(E) = \eta_\varepsilon(S) - 1 \tag{1}$$

Hence, if $\eta_\varepsilon(S) \geqslant 0$, a 1% improvement in energy efficiency leads to less than 1% reduction in energy consumption - or other words, some of the potential energy savings are ‘taken back’ by increased demand for the energy service. In the case of road freight, the energy service could be measured in either vehicle kilometres or tonne kilometres (‘goods moved’) – analogous to the choice between vehicle kilometres or passenger kilometres for car transport (Stapleton et al., 2016).

With the energy service defined as goods moved (tonne kilometres), the appropriate measure of energy efficiency ($\varepsilon = S/E$) is the fuel efficiency of goods moved (tonne kilometres per megajoule – tkm/MJ). Similarly, with the energy service defined as distance travelled (vehicle kilometres – vkm), the appropriate measure of energy efficiency is the fuel efficiency of distance travelled (vehicle kilometres per megajoule – vkm/MJ). In the empirical work below, we choose the first of these measures.

Independent estimates of fuel efficiency are frequently unavailable, or provide insufficient variation to give precise parameter estimates. Hence, an alternative approach is to estimate the rebound effect from one of three *price* elasticities, namely:

- the elasticity of goods moved with respect to the fuel cost of goods moved – $\eta_{p_S}(S)$;
- the elasticity of goods moved with respect to the price of fuel – $\eta_{p_E}(S)$; and
- the elasticity of fuel consumption with respect to the price of fuel – $\eta_{p_E}(E)$.

Where p_E is the price of fuel (£/MJ) and $p_S = p_E/\varepsilon$ is the fuel cost per kilometre (£/km). Under certain assumptions, the negative of each of these price elasticities can considered equivalent to the efficiency elasticity of goods moved (Sorrell and Dimitropoulos, 2007; Stapleton et al., 2016). But since the required assumptions are rather restrictive (especially for $\eta_{p_E}(E)$), there is a need for caution when comparing the results of studies that use different metrics for the rebound effect (Stapleton et al., 2016).

To illustrate the factors influencing fuel efficiency and freight transport, it is useful to decompose the fuel efficiency of goods moved (ε) as follows (Sorrell et al., 2008, 2009):

$$\varepsilon = \frac{TKM}{E} \equiv \frac{TKM}{VKM}\frac{VKM}{VKMT}\frac{VKMT}{E} \tag{2}$$

Or:

$$\varepsilon = lm\varepsilon_V \tag{3}$$

where E is HGV fuel consumption (megajoules - MJ), $VKMT$ is total distance travelled by HGVs (vehicle kilometres); VKM is distance travelled by loaded HGVs (vehicle kilometres); ε_V is the average fuel efficiency of distance travelled by (loaded and unloaded) HGVs (vehicle kilometre per MJ); m is the fractional amount of ‘empty running’ ($m \leqslant 1.0$); and l is the average payload weight of the vehicle fleet (tonnes). The fuel efficiency of goods moved therefore depends upon the fuel efficiency of distance travelled (ε_V), the amount of empty running (m) and the average load factor of vehicles (on a weight basis - l). These in turn depend upon the mix of different weight categories of vehicle within the fleet, the mix of commodities carried, the organisation of logistics, the amount of packaging

Table 1
Empirical estimates of the rebound effect in road freight.

Study	Country and data	Specification	Rebound measure	Rebound estimate	Notes
Winebrake et al. (2015a)	US Aggregate time series 1980–2012	Constant elasticity First difference and error correction	$\eta_{p_E}(S)$ $S = VKM$	~0% Short run Coefficient not significant	Controls for per capita wealth, housing construction and congestion
Winebrake et al. (2015b)	US Aggregate time series 1970–2012	Constant elasticity First difference	$\eta_{p_E}(E)$ and $\eta_{p_E}(S)$ $S = VKM$	~0% Short run Coefficient not significant	Controls for per capita wealth, housing construction, congestion and freight deregulation
Wang and Lu (2014)	China Aggregate panel (31 provinces) 1999–2011	Constant elasticity Static (co-integrated)	$\eta_{p_E}(S)$ $S = TKM$	84% Long-run	Controls for sale of consumer goods and road congestion
Matos and Silva (2011)	Portugal Aggregate time series 1987–2006	Constant elasticity Static 2SLS with ε as instrument for p_S	$\eta_\varepsilon(S)$ $S = TKM$	24% Long-run	Controls for per capital GDP and oil price.
De Borger and Mulalic (2012)	Denmark Aggregate time series 1980–2007	Constant elasticity Structural equations for five variables 3SLS	$\eta_\varepsilon(E)$ $S = VKM$	17% Long-run (10% short run)	Structural model captures linkages between freight demand, fleet characteristics (e.g. capacity, age) and fuel use
Leard et al. (2015)	US Vehicle use survey – five waves of 100 k trucks 1977–2002	Constant elasticity	$\eta_\varepsilon(S)$ $S = VKM$	30% tractor trailers and 9% 'vocational' trucks Long-run	Large micro dataset allows inclusion of a large number of variables and provides robust estimates
Ruzzenenti and Basosi (2017)	EU-28 Aggregate time series 1998–2011	Linear Static	$\eta_\varepsilon(S)$ $S = TKM$	Mean estimate of 55% Long run	Equations estimated for each country. Most estimates insignificant and of indeterminate sign

employed (volume to weight ratio), the fuel efficiency of the individual vehicles, driving patterns, the amount of road congestion and other factors.

As shown by Sorrell et al. (2009, 2012), the historical shift towards larger vehicles in the UK has been associated with a reduction in the average fuel efficiency of distance travelled (vehicle kilometre per MJ) but an improvement in the average fuel efficiency of goods moved (tonne kilometre per MJ) owing in part to increases in the average payload weight. But since the variables in Eq. (3) (an identity) are endogenous, their trends are interdependent – so for example, the fuel efficiency of distance travelled depends upon average payload weight.

The complexity of these relationships has yet to be captured in the limited number of studies that have estimated rebound effects for road freight transport - summarised in Table 1. This table illustrates the different choices that have been made for the measure of the energy service provided by road freight (vkm or tkm), the measure of the rebound effect ($\eta_\varepsilon(S)$, $\eta_{p_S}(S)$, $\eta_{p_E}(S)$, or $\eta_{p_E}(E)$), the type of data, the specification of the model and the estimation method. This variation may in turn have contributed to the diversity of results. For example, two studies of US road freight using aggregate time series data (Winebrake et al., 2015a,b) failed to find any evidence for a rebound effect, while a comprehensive study using survey data from over 100,000 vehicles estimated a rebound effect of 30% (Leard et al., 2015). A more recent study for the EU used a very different methodological approach (stochastic frontier analysis) and obtained a relatively low estimate for the rebound effect (4%) (Llorca and Jamasb, 2017). However, their results for individual countries are highly variable (up to 62%) and it is difficult to judge the reliability of their approach. Five of the seven studies in Table 1 use aggregate time series data and we do the same in what follows - since disaggregate data is not available for the UK. But this choice significantly constrains the type of analysis that can be conducted.

3. Methodology

We estimate a total of 25 models, using different combinations of the variables listed in Table 2. Our explained variable (S_t) for each model is goods moved (tonne kilometres) by HGVs within the UK - including both UK and foreign registered vehicles. We first estimate four *base* models and then 21 *variants* of those models.

3.1. Base models

We estimate two types of base model. The first type (efficiency and fuel price) specifies goods moved (S_t in tonne kilometres) as a function of real per capita GDP (Y_t in 2014 £), the fuel efficiency of goods moved (ε - in tonne kilometres per MJ) and real fuel prices (p_E - in £ per MJ), while the second type (fuel cost) specifies goods moved as a function of real per capita GDP (Y_t) and the real fuel cost of goods moved ($p_S = p_E/\varepsilon$ in £ per tonne kilometre).

Table 2
Variable definitions.

Type	Variable	Symbol	Units	Expected sign
Explained	Goods moved	S_t	Tonne kilometres per capita	
Explanatory	GDP per capita	Y_t	£	Positive
	Manufacturing share of GDP	M_t	$0 \leqslant M_t \leqslant 1$	Positive
	Fuel efficiency of goods moved	ε_t	tonne kilometres per MJ	Positive
	Fuel price	p_{E_t}	£ per MJ	Negative
	Fuel cost of goods moved	p_{S_t}	£ per tonne kilometre	Negative
	Weight regulation dummy	D_{1_t}	0 if $t < 1983$; 1 if $t > 1983$	Positive
	Rail deregulation dummy	D_{2_t}	0 if $t < 1997$; 1 if $t > 1997$	Negative
	Freight deregulation dummy	D_{3_t}	0 if $t < 1993$; 1 if $t > 1993$	Positive

The second specification imposes the hypothesis that freight operators respond in the same way to improvements in the fuel efficiency of goods moved as to reductions in fuel prices, while the first specification allows this hypothesis to be tested. A similar hypothesis is frequently employed in studies of rebound effects in road passenger transport, where efficiency is measured in vehicle or passenger kilometres per MJ (Stapleton et al., 2016). However, several studies have found only limited support for this hypothesis (Greene, 2012; Small and Van Dender, 2007; Stapleton et al., 2016) and it may be even less likely to hold in the freight context owing to the much wider range of factors influencing the fuel efficiency of goods moved (ε).

We estimate both *static* and *dynamic* versions of each type of model. Static models specify distance travelled as a function of the explanatory variables in the same time period – thereby implicitly assuming that the observed demand is in equilibrium. But since responses to efficiency improvements and fuel price changes take time, these models may not adequately capture long-run adjustments. Hence we also investigate dynamic models that specify goods moved as a function of both current and historic values of the explained variables. To conserve degrees of freedom we use a 'partial adjustment' specification that simply adds a one period lag of the explained variable. In both cases we choose a constant elasticity formulation. The base models are then:

Static efficiency and fuel price:

$$\ln S_t = \beta_0^{SE} + \beta_1^{SE}\ln Y_t + \beta_2^{SE}\ln\varepsilon_t + \beta_3^{SE}\ln p_{E_t} + u_t \tag{4}$$

Dynamic efficiency and fuel price:

$$\ln S_t = \beta_0^{DE} + \beta_1^{DE}\ln Y_t + \beta_2^{DE}\ln\varepsilon_t + \beta_3^{DE}\ln p_{E_t} + \beta_4^{DE}\ln S_{t-1} + u_t \tag{5}$$

Static fuel cost:

$$\ln S_t = \beta_0^{SC} + \beta_1^{SC}\ln Y_t + \beta_2^{SC}\ln p_{S_t} + u_t \tag{6}$$

Dynamic fuel cost:

$$\ln S_t = \beta_0^{DC} + \beta_1^{DC}\ln Y_t + \beta_2^{DC}\ln p_{S_t} + \beta_3^{DC}\ln S_{t-1} + u_t \tag{7}$$

The long-run elasticity of goods moved with respect to the fuel cost of goods moved ($\eta_{p_S}(S)$) is given by β_2^{SC} in the static fuel cost model and $(\beta_2^{DC}/(1-\beta_3^{DC}))$ in the dynamic model. This provides an estimate of the long-run direct rebound effect. Similar estimates can be obtained from the coefficients on ε_t and p_{E_t} in the efficiency and fuel price models.

3.2. Model variants

We then estimate a number of variants of these models, using combinations of four additional variables (Table 2). As noted, trends in goods moved have been influenced by multiple factors over this time period, including: income growth and periodic recessions; changes in economic structure; shifts in the commodity mix; wider sourcing of products; just-in-time distribution; increasing concentration of manufacturing and stockholding; shifts towards heavier goods vehicles; changes in average vehicle load factors; and so on (Lehtonen, 2008; McKinnon, 2007; McKinnon and Woodburn, 1996; Sorrell et al., 2009; Sorrell et al., 2012). However, with only 44 years of aggregate time-series data, we are only able to test a limited number of variables.

Following Wadud (2016), we adopt a very simple approach, testing only four additional variables. The first of these is the percentage share of manufacturing in UK GDP. Domestic manufacturing requires transport of raw materials, components and sub-assemblies while imports only require transport of final goods. Also, most of the growth sectors of the UK economy, such as financial services, require only minimal freight transport. Since the share of manufacturing in UK GDP has declined from one third in 1970 to ~10% in 2014, we would expect freight demand to have become partially decoupled from GDP (Sorrell et al., 2009, 2012).

The remainder are binary dummy variables representing exogenous factors that we expect to have influenced road freight demand over this period. We introduce these as covariates (changing the intercept) rather than interactions with GDP (changing the slope), with each variable taking a value of 0 before and 1 after the event.

The first dummy variable (D_{1_t}) represents the change in the UK weight regulations for HGVs in 1983. Following the Armitage report (Armitage, 1980), the UK government increased the weight limit from 32 tonnes (4 axle) to 38 tonnes (5 axle). This triggered a

Table 3
Modelling sequence for each type of model.

Stage	Efficiency and fuel price		Fuel costs	
	Static	Dynamic	Static	Dynamic
1	Base model (1)	Base model (8)	Base model (14)	Base model (21)
2	Manufacturing share variant (2)	Manufacturing share variant (9)	Manufacturing share variant (15)	Manufacturing share variant (22)
3	HGV weight regulation variant (3)	HGV weight regulation variant (10)	HGV weight regulation variant (16	HGV weight regulation variant (23)
4	Rail freight deregulation variant (4)	Rail freight deregulation variant (11)	Rail freight deregulation variant (17)	Rail freight deregulation variant (24)
5	Road freight deregulation variant (5)	Road freight deregulation variant (12)	Road freight deregulation variant (18)	Road freight deregulation variant (25)
6	Reduced variant (6)	Reduced variant (13)	Reduced variant (19)	*Reduced variant (not used)*
7	CCR variant (7)		CCR variant (20)	
No. of models	**7**	**6**	**7**	**5**

Note: Model number in brackets

rapid shift towards > 33 tonne vehicles, owing in part to their lower cost of goods moved. By as early as 1990, > 33 tonne vehicles accounted for more than half of goods moved and this had increased to 74% by 2014. The weight regulations were increased again in 1999 and in 2001 (to 44 tonnes),[1] but the incremental impact of these later changes appears much smaller.

The second dummy variable (D_{2_t}) represents, in part, the privatisation of UK rail freight services that was completed in November 1997. Rail improved in competitiveness and accounted for a larger share of UK goods moved after that date, suggesting a substitution away from road. However, since the trend break in the growth of road freight around 1997 appears larger than can be explained by rail substitution alone (McKinnon, 2007; Sorrell et al., 2009; Sorrell et al., 2012), this dummy may act as a proxy for a number of influencing variables.

The third dummy variable (D_{3_t}) represents the combined effect of completing deregulation of EU road haulage in 1993 and the contemporaneous opening of the Channel tunnel. Prior to deregulation, EU freight traffic relied upon bilateral agreements that limited the timing and duration of journeys. The deregulation process began in 1987 and was completed in 1993 with the introduction of five-year licenses allowing carriers to transport goods anywhere within the EU. Lafontaine and Valeri (2009) found that deregulation had a large positive effect on the growth of international trucking in the EU alongside a reduction in empty running. This effect could have been amplified in the UK with the opening of the Channel tunnel.

3.3. Modelling sequence and robustness tests

We estimate a total of 25 models, using different combinations of the above variables. These include a total of 13 efficiency and fuel price models and 12 fuel cost models. Of these, 14 are static and 11 dynamic.

The sequence of model estimation is summarised in Table 3, together with the total number of models within each category. The selection of models relies upon the results of a series of diagnostic tests that are described below. The model that scores the highest against these diagnostics tests is carried forward at each stage. For example, if the inclusion of the HGV weight regulation dummy in Stage 3 leads to a model with a higher (lower) robustness score than in Stage 2, then the dummy variable is retained (omitted) in subsequent stages. Stage 6 takes the best performing model and removes variables that are individually or jointly insignificant – thereby creating a ‘reduced’ specification. The latter variant is not used for the dynamic fuel cost model, since all variables in the best performing model are significant. With this variant omitted, this gives a total of 25 models.

At each stage, we conduct a comprehensive set of 13 diagnostic tests and use the results to form an overall *robustness score* (0–100%) - with higher scores indicating ‘better’ models. The relevant tests and the associated scores are summarised in Table 4. We test two different weighting rules: the first based on our judgement of the relative importance of each test, and a second giving equal weighting to each test. However, we find the ranking of models is the same in each case.

With time series data, there is a risk of spurious regressions if one of more of the variables is non-stationary. But it is possible for two or more non-stationary variables to be co-integrated, implying there is a stable, long-run relationship between them. We therefore test the residuals of the static models for unit roots. If the results suggest the variables are cointegrated, we re-estimate the ‘best performing’ static model using a specialised technique – ‘canonical cointegrating regression’ (CCR) (Park, 1992) – at Stage 7. For this stage, we use the more limited set of six diagnostic tests summarised in Table 5.

4. Data

Our primary source of data on goods moved over the period 1970–2014 is the Transport Statistics for Great Britain (TSGB) (DfT,

[1] The changes in 1999 permitted 40 tonne (5 axle) and 41 tonne (6 axle) vehicles. The changes in 2001 permitted 44 tonne, 6 axle vehicles

Table 4
Diagnostic tests and weighting rules.

No.	Test	Description	Unequal Weighting	Equal Weighting
1	Coefficient signs	Score if all statistically significant coefficients ($p < 0.05$) have the expected signs	2	1
2	Coefficient magnitudes	Score if all statistically significant coefficients have plausible magnitudes	2	1
3	Serial correlation	Score if Lagrange multiplier (Breusch and Pagan, 1980) test with two lags suggests insignificant serial correlation of the residuals	2	1
4	Heteroscedasticity	Score if Lagrange multiplier test (Breusch and Pagan, 1979) suggests insignificant heteroskedasticity of the residuals	1	1
5	Normality	Score if Jarque and Bera (1987) test suggests normally distributed residuals	1	1
6	Multicollinearity	Score if centred variance inflation factors (VIF) test suggest absence of multicollinearity	1	1
7	CUSUM	Score if cumulative sum of recursive residuals is stable over time (Brown et al., 1975)	2	1
8	CUSUM of squares	Score if cumulative sum of recursive squared residuals is stable over time (Brown et al., 1975)	2	1
9	Akaike information criterion	Use Akaike (1974) information criterion (AIC) to evaluate the trade-off between goodness of fit and model complexity in each group of models. Score 1 for rank 1 or 2, 0.66 for rank 3 or 4, 0.33 for rank 5 or 6, zero for rank 7 or 8	Max of 1	Max of 1
10	Hannan and Quinn information criterion	Use Hannan and Quinn (1979) information criterion in a similar manner to AIC	Max of 1	Max of 1
11	Schwarz information criterion	Use Schwarz (1978) information criterion in a similar manner to AIC	Max of 1	Max of 1
12	Ramsey Regression Equation Specification Error Test - RESET-1	Score if inclusion of squares of fitted values of explained variable significantly improves model fit (Ramsey, 1969)	2	1
13	Ramsey Regression Equation Specification Error Test - RESET-2	Score if inclusion of squares *and cubes* of fitted values of explained variable significantly improves model fit (Ramsey, 1969)	2	1

Table 5
Diagnostic tests and weighting rules for CCR estimation.

No.	Name	Description	Unequal Weighting	Equal Weighting
1	Coefficient signs	Score if all statistically significant coefficients ($p < 0.05$) have the expected signs	2	1
2	Coefficient magnitudes	Score if all statistically significant coefficients have plausible magnitudes	2	1
3	Normality	Score if Jarque and Bera (1987) test suggests normally distributed residuals	1	1
4	Multicollinearity	Score if centred variance inflation factors (VIF) test suggest absence of multicollinearity	1	1
5	Stability	Score if Hansen (1992) test suggests stability of coefficient estimates over time	2	1
6	R^2	Use simple R^2 test to evaluate goodness of fit. For equal (unequal) weighting, score 2 (1) if $R^2 > 0.95$ and score 1.75 (0.875) if $R^2 > 0.90$	2	1

2015).[2] Much of this data derives from the Continuing Survey of Road Goods Transport (CSRGT),[3] which is a detailed, annual survey of the UK activity of 200–400 HGVs. The TSGB uses data on the number of GB-registered HGVs to scale these activity estimates up, and then adds estimates of light goods vehicle (LGV) activity to give a time series of *goods moved in the UK by GB-registered HGVs and LGVs* (DfT, 2015).

For our purposes, this time series need to be adjusted in three ways: first, to remove the goods moved by LGVs; second, to add the goods moved by HGVs registered in Northern Ireland (NI); and third, to add the goods moved by foreign-registered HGVs. The last of these is particularly important, since from 1997 onwards foreign-registered HGVs have accounted for increasing proportion of total UK freight activity (McKinnon, 2007; Sorrell et al., 2008).

The UK Road Freight Statistics[4] provide estimates of good moved by LGVs after 1990, but these are more uncertain than the HGV estimates. The data suggest that the LGV share of total goods moved increased from 4% in 1990 to 7.8% in 2014, with most of this growth occurring after 2000 (Fig. 1). No pre-1990 estimates of good moved by LGV are available, although the UK government does publish estimates of HGV and LGV fuel consumption based upon traffic counts and vehicle fuel efficiency estimates (DECC, 2015). These suggest that the ratio of LGV to HGV fuel consumption remained fairly constant between 1970 and 1990 (Fig. 1). For simplicity, therefore, we assume that LGVs accounted for a constant 4% of total goods moved between 1970 and 1990, and we subtract the full time series from the TSGB data to derive HGV-only estimates of goods moved.

The Road Freight Statistics provide estimates of the UK activity of NI-registered HGVs from 2004 onwards,[5] but activity prior to that date needs to be estimated. NI-registered vehicles accounted for an estimated 2.4% of total UK-registered vehicle activity in 2004 and this fraction remained fairly constant up to 2014. Hence, we simply assume that NI-registered vehicles accounted for 2.4% of total UK-registered vehicle activity between 1970 and 2004. This adjustment should have little effect on the estimated coefficients.

Adjusting for the activity of foreign registered vehicles is more important and less straightforward. The relevant activity (in tonne kilometres) includes:

- *International receipt* (U_{Ft}): UK legs of international road transport where the place of unloading of goods is the UK and the place of loading is a different country.
- *International dispatch* (L_{Ft}): UK legs of international road transport where the place of loading of goods is the UK and the place of unloading is a different country
- *Cabotage* (C_{Ft}): Movement of freight by foreign-registered vehicles in which goods are both loaded and unloaded in the UK.[6]

This activity is not regularly monitored in the UK, with only three surveys to date.[7] The 2000 and 2003 surveys were relatively small and confined to a limited number of terminals (DfT, 2004; McKinnon, 2007), but the 2009 survey was larger (> 3000 vehicles) and more comprehensive (Dft, 2009). The results suggest that foreign-registered vehicles accounted for 8400 million tonne kilometres in the UK in 2009, equivalent to 6.5% of the goods moved by UK-registered vehicles. The majority (63%) of this activity related to imported goods (Table 6).

The Road Freight Statistics provide a time series of the *number* of UK and foreign-registered vehicles travelling *to* mainland Europe from 1983 onwards (N_{Ft}). This indicates a major increase in foreign-registered vehicle activity after 1997, with some of this activity displacing that by UK-registered vehicles (Fig. 2). Pre-1983 activity of foreign registered vehicles can be estimated rather crudely by extrapolating the 1983–87 trend back to 1970. If we further assume that: (a) the relative *proportion* of different activities remained at the level indicated in Table 6 over the full time period; and (b) the volume of each activity was proportional to the number of foreign-registered vehicles travelling *to* mainland Europe, then a time series of the goods moved by foreign-registered vehicles (S_{Ft}) can be estimated from:

[2] https://www.gov.uk/government/collections/road-freight-domestic-and-international-statistics2.
[3] https://www.gov.uk/government/statistics/continuing-survey-of-road-goods-transport-gb-respondents-section3.
[4] https://www.gov.uk/government/collections/road-freight-domestic-and-international-statistics4.
[5] File RFS0144, available at: https://www.gov.uk/government/statistical-data-sets/rfs01-goods-lifted-and-distance-hauled5.
[6] We ignore cross trade, where goods are neither loaded nor unloaded in the UK. This activity is relatively small in the UK and would be expected to have a weaker link to UK GDP.
[7] The International Road Haulage Statistics and Eurostat provide estimates of goods moved and distance travelled on the full international journey, but do not isolate the UK leg of those journeys.

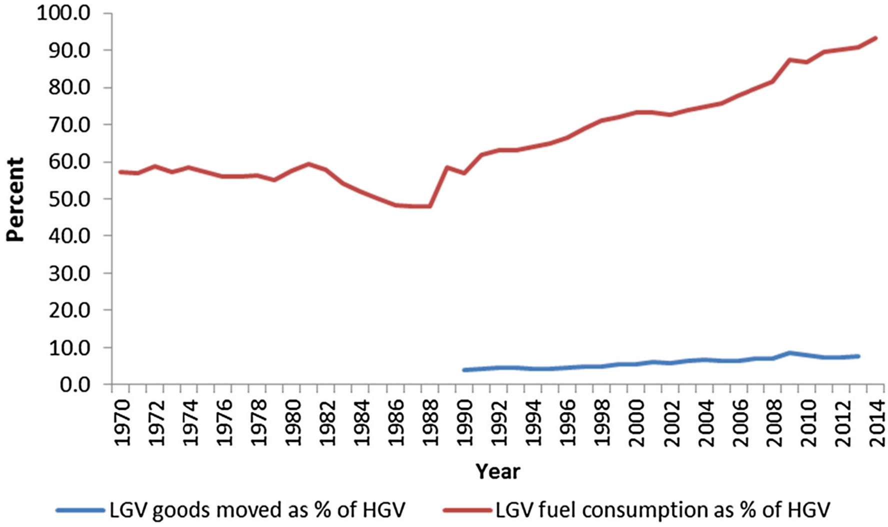

Fig. 1. HGV and LGV share of goods moved and fuel consumption.

Table 6
Estimates of goods moved in the UK by foreign registered vehicles in 2009.

Category	Million tonne kilometres	Percentage of goods moved by foreign-registered vehicles	Percentage of goods moved by UK-registered vehicles
Unloaded in the UK (U_{Ft})	5323	63.4%	4.1%
Loaded in the UK (U_{Ft})	2825	33.6%	2.2%
Cabotage in the UK (C_{Ft})	252	3.0%	0.2%
Total	***8400***	*100.0%*	*6.5%*

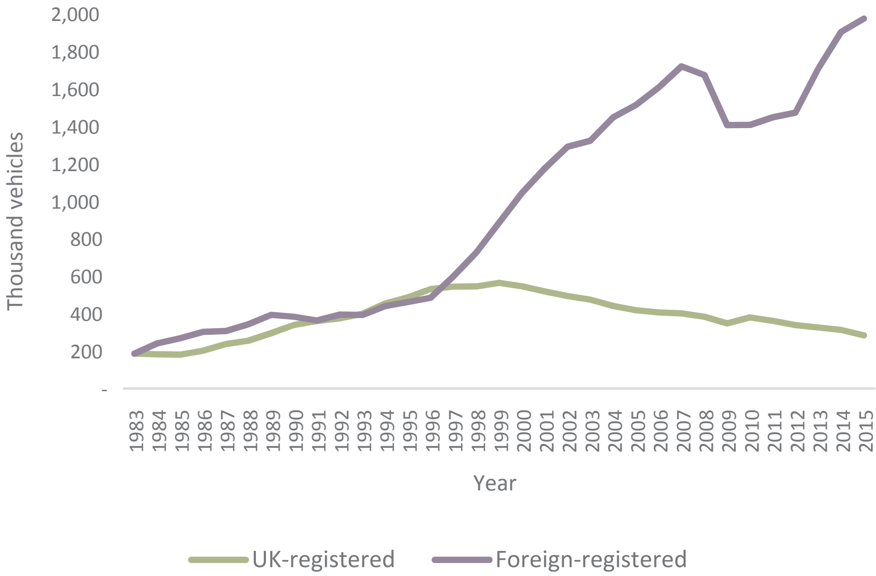

Fig. 2. Number of HGVs travelling from the UK to mainland Europe.

$$S_{Ft} = \frac{N_{Ft}}{N_{F2009}} * (U_{Ft} + L_{Ft} + C_{Ft}) \tag{8}$$

These estimates can then be added to data for UK-registered vehicles to produce a time series of *goods moved in the UK by all types of HGVs*. Data on UK GDP (2014) and population over the period 1970–2014 can be obtained from the UK Office of National Statistics[8] and

[8] https://www.ons.gov.uk/economy/grossdomesticproductgdp8.

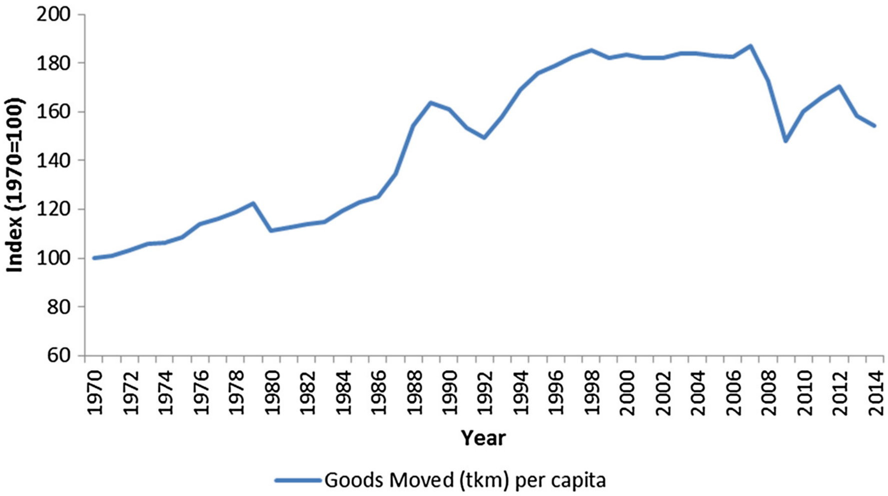

Fig. 3. Goods moved (tonne km) per capita 1970–2014 (index).

combined to give a time series of per capita GDP. Since a full time series of the manufacturing share of UK GDP is difficult to obtain from the Office of National Statistics (ONS), we take estimates from the UN instead.[9] For fuel efficiency, we take data on diesel consumption (E_t - in MJ) by HGVs in the UK from DECC (2015) and combine this with our goods moved data series to estimate the average fuel efficiency of goods moved ($\varepsilon_t = S_t/E_t$- in tonne kilometres per MJ). Although widely used in studies of aggregate transport demand, this approach depends upon the accuracy of the HGV fuel consumption estimates. And since fuel use by HGVs is not independently monitored, this could be a source of bias. However, provided the method used for estimating HGV fuel use has not changed over time, the identified trends in fuel efficiency should be relatively unaffected. Moreover, since independent measures of these variables are not available for the UK, we have little alternative.[10]

To construct a time series for fuel prices (p_{E_t} in £/MJ) we take nominal diesel prices from Department for Business, Energy and Industrial Strategy (BEIS)[11] and convert these to 2014 prices using a GDP deflator from HM Treasury[12]. We then form our time series of the fuel cost of goods moved by dividing fuel prices by the fuel efficiency of goods moved ($p_{S_t} = p_{E_t}/\varepsilon_t$- in £/tkm).

Trends in each of these variables are illustrated in Figs. 3–6. Fig. 3 shows that goods moved per capita rose fairly steadily between 1970 and 1998, then plateaued and fell sharply after the 2007 financial crisis. In 2014, goods moved per capita was 43% higher than 1970, compared to 75% higher in 2007. In absolute terms, goods moved totalled 136 billion tonne kilometres in 2014, compared to 85 billion tonne kilometres in 1970 - an increase of 60%.

Fig. 4 shows that, in real terms, UK per capita GDP in 2014 was 2.3 times larger than in 1970, but per capita manufacturing GDP was 13% lower – with the relative decline of manufacturing accelerating after 1997. This highlights the dramatic restructuring of the UK economy that has occurred over the last 25 years which may be expected to have contributed to the relative decoupling of freight activity from GDP. Note also that the post-1997 trend is correlated with other variables affecting freight transport, including the shift towards foreign registered vehicles (Fig. 2).

Fig. 5 illustrates the estimated trend in the fuel efficiency of goods moved (MJ per tonne kilometre) over this period. As noted earlier, this measure is influenced by a number of variables and it is notable that fuel efficiency began to improve after larger vehicles ($>$ 33 tonne) began to penetrate the UK fleet in the mid-1980s. Fuel efficiency is correlated with fuel prices which also began to increase from the mid-1980s onwards (Fig. 6). While road fuel prices are influenced by fluctuations in international oil prices, the impact of the latter is dampened by the high taxation of road fuels in the UK.[13] Increasing fuel prices raises the fuel cost per tonne kilometre while improving efficiency reduces it – so countervailing trends in these variables reduce the range of variation in the fuel cost per tonne kilometre. Overall, all three of these variables take only a limited range of values over our time period, with fuel efficiency being approximately 10% higher in 2014 than in 1970, and with fuel prices and fuel cost per tonne kilometre being approximately 25% higher. As a result, the variance of our estimated coefficients is likely to be relatively large.

5. Results

5.1. Model fit and diagnostic tests

The results of the diagnostic tests are summarised in Tables A1–A4 in Annex A. Table A1 indicates the aggregate 'robustness score' of the static models together with the variables included at each stage, while Table A2 presents the results of the diagnostic tests.

[9] http://unstats.un.org/unsd/snaama/downloads/Download-GDPcurrent-USD-countries.xls9.
[10] See Schipper et al. (1993) for a discussion of the difficulties with this approach.
[11] https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/244670/qep413.xls11.
[12] https://www.gov.uk/government/statistics/gdp-deflators-at-market-prices-and-money-gdp-March-2015-quarterly-national-accounts12.
[13] This contrasts to North America, where movements in international oil prices have a much larger impact on fuel costs per kilometre.

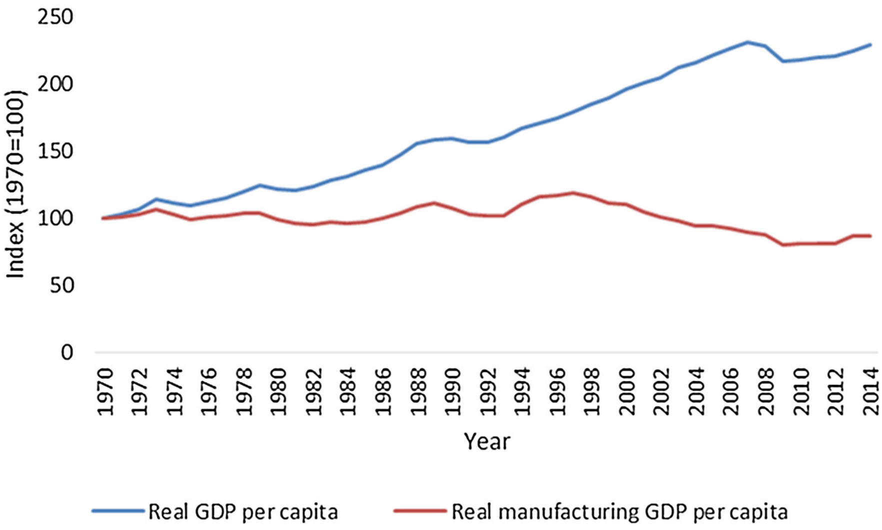

Fig. 4. Real GDP per capita and real manufacturing GDP per capita 1970–2014 (index).

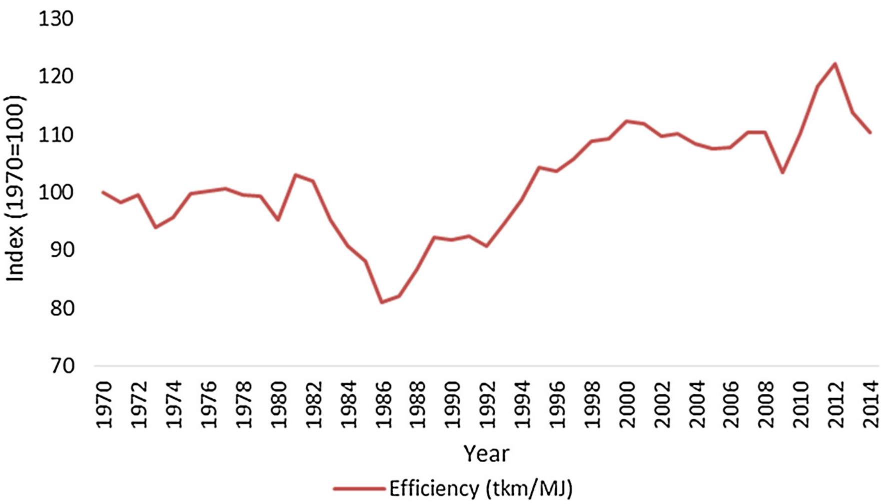

Fig. 5. Fuel efficiency of goods moved (tkm/MJ) 1970–2014 (index).

Tables A2 and A3 do the same for the dynamic models.

Looking first at the static efficiency and fuel price models (1)–(7), we note that the overall robustness scores are relatively high, with the 'best' specification (model 4) scoring 75% (77%). The VIF test suggests the absence of multicollinearity and the RESET tests provides no evidence of misspecification (Table A2). However, there is evidence of parameter instability (CUSUM and CUSUM of squares) and all the models suffer from serial correlation. The latter means that the standard errors may be underestimated, although the coefficient estimates should be unbiased. The best performing model in this group (model 4) includes GDP, fuel efficiency of goods moved, fuel price, manufacturing share and the rail policy dummy (D_2).

The overall robustness scores are slightly lower for the static fuel cost models (8–14), with the 'best' specification (model 9) scoring 70% (69%) and with evidence of both heteroscedasticity and serial correlation (Table A2). Including the manufacturing share variable improves the diagnostics score, but including the dummy variables does not. Also, while the fuel cost of goods moved is included in the best performing model, the coefficient is not significant at the 10% level.

Tables A3 and A4 summarise the diagnostic results for the dynamic models. Again, the aggregate scores are relatively high, with the best performing models scoring higher (90%) than the static specifications, despite evidence of multicollinearity and parameter instability. The best performing efficiency and fuel price model (20) includes the lagged dependent variable, fuel efficiency of goods moved, fuel price and the HGV weight dummy but, oddly, does not include GDP. However, GDP is included in the best performing fuel cost model (23) which also scores highly against the diagnostic tests (85%).

Overall, the results indicate some ambiguity over the preferred specification. While the best performing static models include manufacturing share and the rail policy dummy, the best performing dynamic models exclude these variables but include the weight regulation dummy instead.

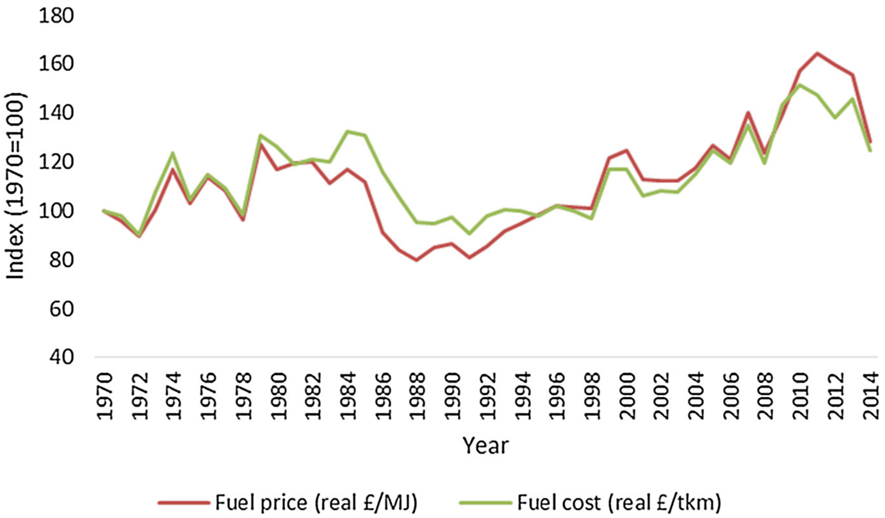

Fig. 6. Real fuel prices (£/MJ) and real fuel costs of goods moved (£/tkm) 1970–2014 (index).

Given the results of the CUSUM tests, we conducted some additional Chow breakpoint tests to investigate whether there was a structural break in the time series. Depending upon the specification used, there was some evidence of a structural break around the mid-1990s. However, splitting the time series into two periods was considered inappropriate, since the reduced degrees of freedom made it difficult to obtain significant estimates. Also, the use of the dummy variables allows for changes in the intercept. Hence, we proceeded with the full time series, but highlight the need for caution when interpreting the results.

5.2. Stationarity properties

It is important to consider the stationarity properties of the models. Tables A5 and A6 summarise the results of two types of unit root tests on the residuals from the static models. The results are borderline (close to the 5% significance level) and contradictory, suggesting the possibility of spurious regressions. However, these results should be interpreted with caution since the tests have only limited power with the number of observations used here. In addition, when we re-estimate the best performing static models (models 4 and 9) with the CCR technique, the Hansen test suggests that the variables are co-integrated – implying a long-run relationship between them, despite the changes in economic and industry structure over this period. If so, the static specification should be preferred over the dynamic specification, despite the slightly lower robustness score. The results of the diagnostic tests for Stage 9 are summarised in Table A7.

5.3. Estimated coefficients

As Table 7 indicates, 21 of the 25 models produced statistically significant estimates of the long-run elasticity of goods moved with respect to GDP. Overall, the results suggest that, ceteris paribus, a 1% increase in GDP was associated with a 0.76% increase in tonne kilometres over this period (range 0.21–0.93%). The mean GDP elasticity from the static models is 36% higher than that from the dynamic models - which is consistent with the interpretation that static models provide long-run equilibrium estimates, while dynamic models provide intermediate-run estimates (Basso and Oum, 2007). However, the estimates from the best performing static and dynamic models are similar.

As Table 8 indicates, 14 out of 22 models produced statistically significant estimates of the long-run elasticity of goods moved with respect to the share of manufacturing in GDP. Overall, the results suggest that a 1% fall in the manufacturing share was associated with a 0.81% reduction in tonne kilometres (range 0.73–0.87%). However, this estimate derives primarily from the static models - only two of the dynamic models produced statistically significant estimates of this coefficient.

Six of the dynamic models produced statistically significant estimates for the HGV weight regulation dummy, but this variable was not significant in the static models (Table 9). Overall, the results suggest that increasing the vehicle weight limits was associated with a 6.2% increase in goods moved (range 3.6–8.9%). In contrast, five models produce statistically significant estimates for the 'rail policy' dummy, but only one of these was a dynamic model. These results suggested that the trend break in 1997 was associated with a 6.8% decrease in goods moved (range 4.2–8.3%). While the increased competitiveness of rail freight contributed to this trend break, a number of other factors must have been involved. No models provided significant estimates of the freight deregulation/channel tunnel dummy variable, but this may be due to collinearity with the rail policy dummy (although we expect these to have opposite signs). Overall, these results should be interpreted with caution since: (a) only a third of the models give significant estimates of the dummy variables; (b) the results from the static and dynamic models are partly contradictory; and (c) the variables act as proxies for a number of complex and correlated developments.

Table 10 summarises our estimates of the long-run elasticity of goods moved with respect to fuel efficiency ($\eta_{\varepsilon}(S)$), fuel prices ($\eta_{p_E}(S)$) and fuel costs ($\eta_{p_S}(S)$). As discussed in Section 2, each of these elasticities may be used as an estimate of the long run rebound effect.

Table 7
Mean estimates of the long-run elasticity of goods moved with respect to GDP.

Static	Dynamic	CCR	Mean
0.84	0.54	0.89	0.76
(11/12)	(8/11)	(2/2)	(21/25)

Note: Each table entry is the mean of the individually or jointly statistically significant estimates in that category, while the numbers in brackets indicate the fraction of relevant models in each category that provided statistically significant estimates.

Table 8
Mean estimates of the long-run elasticity of goods moved with respect to manufacturing share of GDP.

Static	Dynamic	CCR	Mean
0.78	0.83	0.81	0.81
(10/10)	(2/10)	(2/2)	(14/22)

Note: Each table entry is the mean of the individually or jointly statistically significant estimates in that category, while the numbers in brackets indicate the fraction of relevant models in each category that provided statistically significant estimates.

Table 9
Mean estimates of the impact of the dummy variables on goods moved.

Dummy	Static	Dynamic	CCR	Mean
(1) HGV weight	–	6.2%	–	6.2%
	(0/8)	(6/8)	(0/2)	(6/18)
(2) Rail policy	−7.2%	−4.2%	–	−6.78%
	(4/8)	(1/8)	(0/2)	(5/18)
(3) Freight deregulation	–	–	–	–
	(0/8)	(0/8)	(0/2)	

Note: Percentage impact of dummy variable D_n is given by: 100 * [$EXP(D_n)$ − 1]. Each table entry is the mean of the individually or jointly statistically significant estimates in that category, while the numbers in brackets indicate the fraction of relevant models in each category that provided statistically significant estimates.

Overall, 20 of the 25 models produced a statistically significant estimate of one or more of these elasticities, with estimates ranging from 0.21 to 1.38. Averaging across these different estimates leads to an estimated rebound effect of **61%**. The mean estimates of the rebound effect from each of the individual elasticities are as follows:

- **69%** for the elasticity of tonnes moved with respect to fuel efficiency (9 out of 13 models provided significant estimates, ranging from 21% to 138%)
- **57%** for the elasticity of tonnes moved with respect to fuel prices (6 out of 13 models provided significant estimates, ranging from 52% to 67%)
- **57%** for the elasticity of tonnes moved with respect to fuel costs (5 out of 12 models provided significant estimates, ranging from 21% to 82%)

Using only the best performing models, the corresponding estimates are **30%, 58% and 58%** respectively. Averaging across these gives a mean estimate of **49%** - which is lower than the mean of all estimates. The static models produced smaller estimates of these elasticities than the dynamic models, particularly for fuel efficiency. This finding is analogous to that obtained in meta analyses of elasticity estimates for car transport, suggesting that reliance upon static (dynamic) models will lead to smaller (larger) price elasticity estimates (Goodwin et al., 2004). We also observe that the fuel price and fuel cost elasticity estimates are very similar, and the efficiency elasticity estimates are smaller in the case of the static models and larger in the case of the dynamic models. None of the CCR models produced statistically significant estimates of these elasticities.

6. Conclusions

This study has estimated the long-run direct rebound effect for UK road freight over the period 1970–2014. We have investigated 25 different model specifications and estimated the rebound effect using both efficiency and price elasticities. There are three main conclusions.

First, using the mean of the statistically significant estimates from all specification, we estimate a direct rebound effect of **61%,** which is larger than the estimate obtained by six out of the seven previous studies of rebound effects in road freight (Table 1) and almost twice as large as the consensus estimate of direct rebound effects in road passenger transport (Dimitropoulos et al., 2016). Using the mean of the estimates from our most robust models, we estimate a slightly lower direct rebound effect of **49%**. Our

Table 10
Estimates of the long-run elasticity of goods moved with respect to fuel efficiency, fuel prices and fuel costs (measures of the direct rebound effect).

Elasticity	Static	Dynamic	CCR	Mean
$\eta_{\varepsilon}(S)$	**0.35**	**1.12**	–	**0.69**
	(0.21–0.54)	*(0.77–1.38)*		*(0.21–1.38)*
	(5/6)	(4/6)	(0/1)	(9/13)
$\eta_{P_E}(S)$	**0.52**	**0.58**	–	**0.57**
	(0.52)	*(0.54–0.67)*		*(0.52–0.67)*
	(1/6)	(5/6)	(0/1)	(6/13)
$\eta_{P_S}(S)$	**0.51**	**0.59**	–	**0.57**
	(0.51)	*(0.21–0.82)*		*(0.21–0.82)*
	(1/6)	(4/5)	(0/1)	(5/12)
Mean	**0.46**	**0.76**	–	**0.61**
	(0.21–0.54)	*(0.21–1.38)*		*(0.21–1.38)*
	(7/12)	(13/11)	(0/2)	(20/25)

Note: First entry in each cell is the mean of the individually or jointly statistically significant estimates in that category. Second entry is the range of statistically significant estimates. Third entry is the fraction of relevant models in that category that provided significant estimates.

estimates are also fairly consistent between different model specifications and between different metrics for estimating the rebound effect, although individual estimates range from 21% and 137%.

If correct, this implies that a significant proportion of the potential energy and carbon savings from improved efficiency in UK road freight has been taken back by increased freight activity (more tonne kilometres). A possible explanation for such a large rebound is that operators are highly sensitive to fuel costs since these account for around a third of total operating costs – although the limitations of our methodology (see below) suggests the need for caution with such an interpretation. But if correct, it highlights the importance of fuel taxation for achieving energy and carbon savings in this sector.

Second, it is difficult to reliably estimate the rebound effect in UK road freight because the range of variation in both the fuel efficiency of goods moved and the fuel cost of goods moved has been relatively modest over the last 45 years. This contrasts to the US, where differences in the vehicle mix and lower taxation of road fuels has contributed to larger variation in these variables. Also, the steady increase in the fuel efficiency of goods moved since the mid-1980s has acted to offset the steady increase in fuel prices over the same period.

Third, we find evidence that increases in the vehicle weight limits have encouraged more freight activity, but other studies suggest that these have also contributed to improvements in the fuel efficiency of goods moved (Sorrell et al., 2009, 2012). While the decline of UK manufacturing has contributed to a decoupling of UK road freight from GDP, an increasing proportion of UK road freight is being undertaken by foreign registered vehicles (Sorrell et al., 2009, 2012). More generally, the complexity of factors influencing both the demand for road freight and the fuel efficiency of road freight makes it difficult to isolate the impact of individual variables.

Overall, methodological and data limitations severely constrain the range of variables that we can test for with this approach, as well as the level of confidence that we can have in our results. For example, given the far-reaching changes in the UK economy and the logistics industry over this period, it seems likely that the magnitude of the rebound effect has changed over time. But our tests for this proved inconclusive.[14] In addition, our use of aggregate time series data severely limits the degrees of freedom available; there are considerable uncertainties associated with the amount of goods moved by LGVs and foreign registered vehicles; problems may be created by the inter-dependence of our fuel efficiency and fuel consumption estimates (Schipper et al., 1993); we have not tested for possible asymmetric responses to changes in fuel prices (Dargay, 2007); and our use of a lagged dependent variable in the dynamic models may potentially introduces bias (Keele and Kelly, 2006). Problems such as these are common to most econometric studies of road freight that use aggregate time series data and are only partially mitigated by our systematic use of diagnostic tests. Hence, more reliable estimates of rebound effects in this sector are likely to be contingent upon the availability of more disaggregated data sources, such as from vehicle use surveys.

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Appendix A

Tables A1–A7.

[14] We experimented with some interaction terms between per capita GDP and price/efficiency, but these were found to be insignificant and did not improve model performance.

Table A1
Robustness score and inclusion of variables– static models.

Type	Model	Score 1	Score 2	$\ln Y_t$	$\ln \varepsilon_t$	$\ln p_{E_t}$	$\ln p_{S_t}$	$\ln M_t$	D_{1t}	D_{2t}	D_{3t}
Fuel efficiency and fuel price	1	53	58	*	*	*					
	2	70	69	*	*	*		*			
	3	63	58	*	*	*		*	*		
	4	**75**	**77**	*	*	*		*		*	
	5	73	73	*	*	*		*		*	*
	6	75	77	*	*			*		*	
	7	*53*	*58*	*	*	*		*		*	
Fuel cost	8	63	65	*			*				
	9	**70**	**69**	*			*	*			
	10	63	58	*			*	*	*		
	11	70	69	*			*	*		*	
	12	63	58	*			*	*			*
	13	70	69	*				*			
	14	*90*	*83*	*			*	*			

Note: Best performing models in each group highlighted in bold. Models 7 and 14 use a different set of diagnostic tests, so their score is not comparable to the other models.

Table A2
Results of diagnostic tests – static models.

Model	Coefficients		Standard				Stability		Parsimony			Functional Form		Robustness score 1 (%)	Robustness score 2 (%)
	Signs⌂	Magnitudes⌂	No serial correlation	Homoscedasticity	Normality	No imperfect multicollinearity	CUSUM	CUSUM of Squares	Akaike Icriterion	Schwarz criterion	Hannan-Quinn	RESET 1	RESET 2	Aggregated unequally weighted performance	Aggregated equally weighted performance
1	Pass	Pass	Fail	Pass	Pass	Pass	Fail	Fail	6	6	6	Pass	Fail	53%	58%
2	Pass	Pass	Fail	Pass	Fail	Pass	Pass	Fail	5	3	4	Pass	Pass	70%	69%
3	Pass	Pass	Fail	Pass	Fail	Fail	Pass	Fail	4	5	5	Pass	Pass	63%	58%
4	**Pass**	**Pass**	**Fail**	**Pass**	**Fail**	**Pass**	**Pass**	**Fail**	**1**	**2**	**1**	**Pass**	**Pass**	**75%**	**77%**
5	Pass	Pass	Fail	Pass	Fail	Pass	Pass	Fail	3	4	3	Pass	Pass	73%	73%
6	Pass	Pass	Fail	Pass	Fail	Pass	Pass	Fail	2	1	2	Pass	Pass	75%	77%
8	Pass	Pass	Fail	Pass	Pass	Pass	Pass	Fail	6	6	6	Pass	Fail	63	65
9	**Pass**	**Pass**	**Fail**	**Fail**	**Fail**	**Pass**	**Pass**	**Fail**	**1**	**2**	**1**	**Pass**	**Pass**	**70**	**69**
10	Pass	Pass	Fail	Fail	Fail	Pass	Pass	Fail	4	4	4	Pass	Pass	63	58
11	Pass	Pass	Fail	Fail	Fail	Pass	Pass	Fail	2	3	3	Pass	Pass	70	69
12	Pass	Pass	Fail	Fail	Fail	Pass	Pass	Fail	5	5	5	Pass	Pass	63	58
13	Pass	Pass	Fail	Fail	Fail	Pass	Pass	Fail	3	1	2	Pass	Pass	70	69

Notes: Best performing models in each group highlighted in bold. Cointegrating variant (model 14) not included.

Table A3
Robustness score and inclusion of variables– dynamic models.

Type	Model	Score 1	Score 2	$\ln S_{t-1}$	$\ln Y_t$	$\ln \varepsilon_t$	$\ln p_{E_t}$	$\ln p_{S_t}$	$\ln M_t$	D_{1t}	D_{2t}	D_{3t}
Fuel efficiency and fuel price	15	73	65	*	*	*	*					
	16	70	69	*	*	*	*		*			
	17	85	85	*	*	*	*			*		
	18	68	65	*	*	*	*			*	*	
	19	68	65	*	*	*	*			*		*
	20	**90**	**92**	*		*	*			*		
Fuel cost	21	75	69	*	*			*				
	22	70	69	*	*			*	*			
	23	**80**	**77**	*	*			*		*		
	24	63	58	*	*			*		*	*	
	25	78	73	*	*			*		*		*

Note: Best performing models in each group highlighted in bold.

Table A4
Results of diagnostic tests – dynamic models.

Model	**Coefficients**		**Standard**				**Stability**		**Parsimony**			**Functional Form**		**Robustness score 1**	**Robustness score 2**
	Signs[⌂]	Magnitudes[⌂]	No serial correlation	Homoscedasticity	Normality	No imperfect multicollinearity	CUSUM	CUSUM of Squares	Akaike Icriterion	Schwarz criterion	Hannan-Quinn	RESET 1	RESET 2	Aggregated **unequally weighted** performance	Aggregated **equally weighted** performance
15	Pass	Pass	Pass	Pass	Fail	Fail	Pass	Fail	6	4	6	Pass	Pass	73	65
16	Pass	Pass	Fail	Fail	Pass	Fail	Pass	Fail	1	1	1	Pass	Pass	70	69
17	Pass	Pass	Pass	Pass	Pass	Fail	Pass	Fail	3	3	3	Pass	Pass	85	85
18	Pass	Pass	Pass	Pass	Pass	Fail	Fail	Fail	4	5	4	Pass	Pass	68	65
19	Pass	Pass	Pass	Pass	Pass	Fail	Fail	Fail	5	6	5	Pass	Pass	68	65
20	**Pass**	**Pass**	**Pass**	**Pass**	**Pass**	**Pass**	**Pass**	**Fail**	**2**	**2**	**2**	**Pass**	**Pass**	**90**	**92**
21	Pass	Pass	Pass	Pass	Fail	Fail	Pass	Fail	4	2	4	Pass	Pass	75	69
22	Pass	Pass	Fail	Fail	Pass	Fail	Pass	Fail	1	1	1	Pass	Pass	70	69
23	**Pass**	**Pass**	**Pass**	**Pass**	**Fail**	**Fail**	**Pass**	**Fail**	**3**	**3**	**2**	**Pass**	**Pass**	**80**	**77**
24	Pass	Pass	Pass	Pass	Fail	Fail	Fail	Fail	5	5	5	Pass	Pass	63	58
25	Pass	Pass	Pass	Pass	Fail	Fail	Pass	Fail	2	4	3	Pass	Pass	78	73

Note: Best performing models in each group highlighted in bold.

Table A5
Results of unit root tests on residuals - static efficiency and fuel price models.

Model	Phillips Person	Augmented Dicky Fuller
1. Base	Rejected in levels	Rejected in levels
2. Manufacturing GDP	Rejected in 1d	Rejected in levels
3. Freight policy 1	Rejected in 1d	Rejected in levels
4. Freight policy 2	**Rejected in 1d**	**Rejected in levels**
5. Freight policy 3	Rejected in 1d	Rejected in levels
6. Reduced	Rejected in 1d	Rejected in levels

Note: 'Best performing' specification in bold

Table A6
Results of unit root tests on residuals - static price per kilometre models.

Stage	Phillips Person	Augmented Dicky Fuller
8. Base	Rejected in levels	Rejected in levels
9. Manufacturing GDP	**Rejected in 1d**	**Rejected in levels**
10. Freight policy 1	Rejected in 1d	Rejected in levels
11. Freight policy 2	Rejected in 1d	Rejected in levels
12. Freight policy 3	Rejected in 1d	Rejected in levels
13. Reduced	Rejected in 1d	Rejected in levels

Note: 'Best performing' specification in bold

Table A7
Results of diagnostic tests - CCR model.

	Coefficients		Standard		Stability	Goodness of fit	Robustness score 1	Robustness score 2
Model	Signs⌂	Magnitudes⌂	Normality	No implicit multicollinearity	Hansen test	Goodness of fit	Aggregated **unequally weighted** performance	Aggregated **equally weighted** performance
7	Pass	Pass	Fail	Pass	Pass	Pass (5%)	90%	83%
14	Pass	Pass	Fail	Pass	Pass	Pass (5%)	90%	83%

Appendix B. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.trd.2018.05.006.

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